# The University of Sussex-Huawei locomotion and transportation dataset for multimodal analytics with mobile devices

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# The University of Sussex-Huawei Locomotion and Transportation Dataset for Multimodal Analytics with Mobile Devices

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**ABSTRACT** Scientific advances build on reproducible research which need publicly available benchmark datasets. The computer vision and speech recognition communities have led the way in establishing benchmark datasets. There are much less datasets available in mobile computing, especially for rich locomotion and transportation analytics.

This paper presents a highly versatile and precisely annotated large-scale dataset of smartphone sensor data for multimodal locomotion and transportation analytics of mobile users. The dataset comprises 7 months of measurements, collected from all sensors of 4 smartphones carried at typical body locations, including the images of a body-worn camera, while 3 participants used 8 different modes of transportation in the south-east of the United Kingdom, including in London. In total 28 context labels were annotated, including transportation mode, participant's posture, inside/outside location, road conditions, traffic conditions, presence in tunnels, social interactions, and having meals. The total amount of collected data exceed 950 GB of sensor data, which corresponds to 2812 hours of labelled data and 17562 km of traveled distance. We present how we set up the data collection, including the equipment used and the experimental protocol. We discuss the dataset, including the data curation process, the analysis of the annotations and of the sensor data. We discuss the challenges encountered and present the lessons learned and some of the best practices we developed to ensure high quality data collection and annotation.

We discuss the potential applications which can be developed using this large-scale dataset. In particular, we present how a machine-learning system can use this dataset to automatically recognize modes of transportations. Many other research questions related to transportation analytics, activity recognition, radio signal propagation and mobility modelling can be adressed through this dataset. The full dataset is being made available to the community, and a thorough preview is already published [1].

**INDEX TERMS** Activity recognition, Context awareness, Camera, Intelligent transportation systems, GPS, GSM, Locomotion dataset, Multimodal sensors, Pattern analysis, Sensor fusion, Supervised learning, Transportation dataset, WiFi

## I. INTRODUCTION

The recent technological advances in smartphones allow to collect rich sensor data, which can be used to discover knowledge about the user's activities and context. This enables new applications providing tailored context-aware services to the user [1], [2]. For example, if an intelligent system is aware that the user is driving it can provide traffic information and suggest better routes [3]. In recent years, there have been numerous studies analyzing multimodal sensor data collected from smartphones during locomotion and motorized transportation [4]. Analyzing such multimodal data enables context-aware applications in fields such as localization [5], activity and health monitoring [6], parking spot detection [7], content delivery optimization [8], [9], etc.

While there are numerous datasets related to gait and activity analysis with wearable sensors [10], [11], there are only a limited number of datasets for a more general analysis of locomotion and usage of transportation modes (e.g. public transport, bicycle, etc.). To our knowledge, only two transportation datasets collected with wearable sensors are publicly available. The first one is Microsoft's GeoLife dataset [12], which provides 50176 hours of data collected by 182 users. The dataset however contains only GPS traces which prevents its use in multimodal analytics. The other available dataset is the recent US-Transportation dataset [13], which contains the data of 9 sensors from a smartphone but contains only 31 hours of data. It is recorded with a single smartphone, which prevents using it to assess the effect of device placement on the resulting sensor data. More generally, the lack of a publicly available dataset with sufficient duration, large number of sensor modalities, and rich high-quality annotations obviously holds back research advances in this area.

To overcome this, we designed the University of Sussex-Huawei Locomotion-Transportation (SHL) dataset[1], which aims to be a highly versatile dataset suitable for a wide range of studies in fields such as transportation mode recognition, mobility pattern mining, localization, tracking and sensor fusion. It is designed to support reproducible research through its versatility, multimodality, large size, and its public availability. The availability of such a dataset enables research groups to compare methods on identical data while leaving significant room for wide variety of new studies.

To achieve this versatility, we designed a large-scale longitudinal data collection campaign, and collected 2812 hours of labelled data over a period of 7 months. The SHL dataset contains multimodal locomotion and transportation data, which was recorded by three participants engaging in 8 different modes of transportation in real-life settings, travelling 17562 km in total. Even though the number of participants is three only, our focus was on the multimodality of the collected data, the quality and richness of the annotations, and on the collection of real-life data over a long period of time so that we can also study changes in behavior and usage of transportation modes. Each participant carried four smartphones simultaneously at common body locations, which results in 4x703=2812 hours of annotated data. Each smartphone was logging the data of the 15 sensors available in the smartphone (e.g., inertial sensors, GPS, ambient pressure sensor, ambient humidity). Beside the smartphones, the participants also wore a front-facing camera, which allowed us to verify and correct annotations and to introduce additional post-collection annotations. This resulted in 28 total annotation types, including 8 modes of transportation, the participant's posture, inside/outside location, road conditions, presence in tunnels, social interaction, and having meals. A preview of the dataset is already available, which consists of 4x59=236 hours of labeled data. The complete version of the dataset will be published together with a detailed benchmark of a transportation mode recognition pipeline.

The contributions of the paper are:

- a review of the existing transportation datasets collected with wearable sensors and their characteristics (Section II);
- a detailed description of the data collection procedure and the data quality check-up techniques (Section III);
- the analysis and statistics of the dataset's annotations and the sensors (Section IV);
- an exemplary use of machine learning to recognize modes of transportation (Section V);
- the lessons learned and some of the best practices we developed for data collection, assuring data quality and reducing loss (Section VI);
- a discussion of the other applications which can be developed using this richly-annotated dataset (Section VI).

## II. STATE OF THE ART

In contrast to the numerous datasets for activity recognition and gait analysis [10], [11], the number of datasets that deal with the analysis of locomotion and usage of various transportation modes is rather limited. Table 1 lists the related locomotion and transportation datasets and their characteristics, including the number and type of devices simultaneously worn by the participants during the dataset recording, the type of sensor data collected, the number of participants, the amount of data, the kind of annotations and the availability of the dataset.

There are two datasets which offer more hours of data than the SHL dataset we introduce here. The first is the Microsoft's GeoLife dataset [12], which is one of the largest publicly available datasets (with 50176 traces) but which contains GPS data only. The other is the HTC dataset [14], which has a duration up to 8311 hours but only contains the data from 3 inertial sensors. Even though the authors claimed that a small part of the data is publicly available, we were not able to access it.

[1] Available at www.shl-dataset.org

Table 1: Related locomotion and transportation datasets. The sensors are abbreviated as: Acc for accelerometer, Gyro for gyroscope, and Mag for magnetometer.

| Dataset | Devices worn simultaneously | Sensor data per device | Participants | Labelled data [h] | Annotations | Public |
|---|---|---|---|---|---|---|
| SHL [ours] | 4 smartphones: hand, torso, backpack, trousers; 1 front-facing camera | 15 smartphone sensors (see Table 2); 1 time-lapse video | 3 | 4x703 = 2812 | 28: 18 labels for 8 main transportation activities + 10 labels indicating the road conditions, social interaction, being in a tunnel, traffic information, and having meals (for details see Annotation subsection) | Yes |
| Geolife [12] | 1 GPS logger or 1 GPS phone | GPS | 182 | 50176 | 6: Walk, bus/taxi, bike, car, subway, train | Yes |
| US Transportation [13] | 1 smartphone, no preferred placement | 9 smartphone sensors [13] | 13 | 31 | 5: Walk, car, still, train and bus | Yes |
| HTC [14] | 1 smartphone, no preferred placement | Acc, Gyro, Mag | 224 | 8311 | 10: Still, walk, run, bike, motorcycle, car, bus, metro, train, high-speed rail | No |
| Widhalm [15] | 1 smartphone, no preferred placement | Acc, GPS | 15 | 355 | 8: Bus, car, bike, tram, train, subway, walk, motorcycle | No |
| Hemminki [16] | 1 smartphone, partly no preferred placement, partly fixed locations: trousers, bag, torso | Acc, GPS | 16 | 150 | 6: Still, walk, bus, train, metro, tram | No |
| Zhang [17] | 1 smartphone, no preferred placement | Acc | 15 | 30 | 6: Walk, bike, car passenger, car driver, bus, subway | No |
| Jahangiri [18] | 1 smartphone, no preferred placement | Acc, Gyro, GPS | 10 | 25 | 5: Bike, walk, run, car, bus | No |
| Xia [19] | 1 smartphone, jacket/torso | Acc, Gyro, GPS | 18 | 22 | 4: Walk, bicycle, motor, stand | No |
| Reddy [20] | 6 smartphones, arm, waist, chest, hand, pocket, bag | Acc, GPS, WiFi, GSM | 16 | 6x20 = 120 | 5: Still, walk, run, bike, motor | No |
| Wang [21] | 1 smartphone, no preferred placement | Acc | 7 | 12 | 6: Still, walk, bike, bus, car, subway | No |
| Su [22] | 1 smartphone, no preferred placement | Acc, Gyro, Mag, barometer | 5 | 3 | 6: Walk, run, bike, car, bus, subway | No |
| Siirtola [23] | 1 smartphone, trousers | Acc | 8 | 4 | 5: Still, walk, run, bike, car | No |
| Yang [24] | 1 smartphone, no preferred placement | Acc | 3 | 3 | 6: Sit, Stand, walk, run, bike, car | No |

The SHL dataset which we introduce here and the one collected by Reddy [20] are the only ones that were collected with multiple devices worn by the same participant. This allows to characterize the effect of the placement of the device on various types of analyses (e.g. satellite reception), or to create placement-independent recognition models.

Our SHL dataset contains a significantly larger number of sensors (15 smartphone sensors and a time-lapse video) compared to the others, which mainly contain accelerometer, GPS, and in some cases gyroscope, magnetometer and barometer. The US-Transportation dataset has been published recently and it contains data from 9 sensors collected by a single smartphone, but it has a limited duration of only 31 hours. In the SHL dataset, the wide variety of sensors modalities, and the availability of the sensors at 4 locations simultaneously allows a wide range of analyses about the contribution of combinations of sensors modalities to the problem being addressed. These problems could include transportation recognition, multimodal localization, sensor-based energy-efficiency analysis, energy saving through sensor duty cycling and others.

Our dataset was collected by only three participants, which is less than the other datasets. However, the variability in the sensor signal during transportation is primarily stemming from the motion of the vehicle as the movements of users within a vehicle are constrained (e.g. the movement of the bag containing the smartphone of two distinct users travelling in a bus would be quite similar). Therefore, we emphasized: i) collecting very long travel distance in vehicles at the expense of less users; ii) acquiring multimodal data; iii) rich high-quality annotations. We ensured annotation quality through multiple processes described in this paper, including continuous verification during the data collection campaign by a supervisor researcher.

To summarize, our SHL dataset was collected by 4 smartphones simultaneously, it includes 15 sensors per phone, and it totals 2812 hours of annotated data. This makes it by far the largest publicly available dataset and the most diverse in terms of data sources. Additionally, our dataset is the only one that used a camera to enhance annotations post-collection, which allowed us to provide 28 type of annotations and to guarantee their high quality. This is significantly more than any of the other datasets.

## III. DATA COLLECTION

The data collection process is sketched in Figure 1. First, the three participants (we refer to them as User 1, 2 and 3) were trained to use the dataset collection equipment in order to collect a precise annotated transportation dataset. In order to ensure a balanced dataset, we prepared a weekly outline of the activities (activity scenario) that the users would focus on, but we left the users choice of the activities to carry out for each day. During the execution of the activities, the users were using an Android application to label the appropriate activities and transportation modes. After the data collection, the users used a specialized annotation tool to check and correct the annotations. Finally, the dataset was curated and processed to be released in an easy to use format.

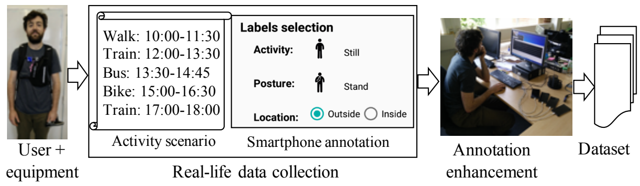


Figure 1: Dataset collection overview.

### A. PARTICIPANT RECRUITMENT

Previous work has shown that data can be collected from volunteers with or without financial incentive [25]. However, to ensure the quality of the data collected and the corresponding annotations, we planned and executed the data collection with participants which were hired as employees of the University. This also provided the participant with insurance coverage (which was fortunately not used).

The participants were chosen after a 45-minute long interview process. During the interview, we explained in significant detail the data collection process to the participant. We believe detailed explanations were instrumental in not having any participant withdrawing from the the data collection. While participants were employed specifically to perform a full-time, precise, and controlled data collection, we also explained them that they could and should attempt to go about their usual daily activities, as they would even without participating in this project, as this would provide a more natural dataset. During the interview, we examined the participants' motivation and reliability. Eventually, the selected participants were hired through the official University recruitment procedure, and in addition signed an informed consent form. The data collection protocol was ethically approved by the University of Sussex (C-REC reference number ER/DR231/1).

### B. DATA COLLECTION EQUIPMENT

Figure 2 shows the equipment that the participants wore, and a screenshot of the mobile phone application developed for the data collection.

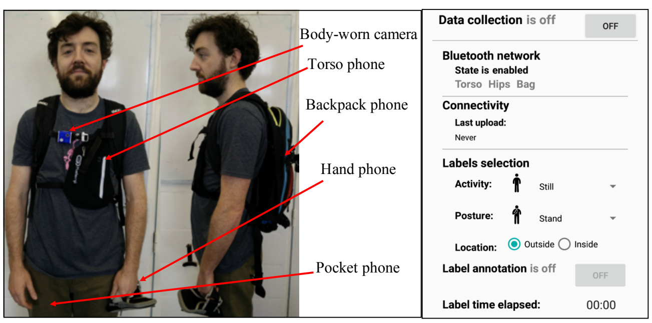


Figure 2: Description of the equipment for data collection. A participant wearing the equipment (on the left), and a screenshot of the smartphone application (on the right).

To ensure a sensor-rich and logistically practical data collection, for each participant we used four high-end HUAWEI Mate 9 smartphones [26]. These phones contain a rich set of sensors, such as inertial sensors with high-sampling rate (>100 Hz), GPS, ambient pressure sensor, ambient humidity sensor, etc. The smartphones were placed on body locations where people are used to wearing phones:

- the 1st phone was held in the hand most of the time. When running or cycling, the phone was carried in an armband on the lower-arm. When the participants did some activity that needed hand engagement, they put the phone in the armband. In the dataset this location is referred to as "Hand";
- the 2nd phone was carried in a jacket breast pocket (if available) or on a chest strap (as shown in Figure 2) or on the upper abdomen for User 3. In the dataset this location is referred to as "Torso";
- the 3rd phone was carried in the trousers front pocket. This location is referred as "Hips" in the dataset;
- the 4th phone was carried in a backpack. The User 3 sometimes wore this phone in a side bag. The corresponding data is referred to as "Bag" in the dataset.

The rationale for this sensor placement was to collect data from as many typical locations where phones are carried, so that the analysis and the models created on this dataset are general and cover most real-life situations.

Additionally, the participants wore a front-facing body camera, which was used to verify label quality during a post-collection annotation procedure. As a part of the dataset it will allow vision-based applications, such as object recognition. The camera was worn on the chest or backpack straps, generally facing the forward direction. In the car, we asked the participants to orient the camera to take pictures of the road, which later helped them to annotate the road condition and the presence in tunnels. The camera was set to take pictures at regular interval every 30 seconds, which is frequent enough to help the participant to recall the data collection details during the course of the day and, meanwhile, is less invasive to surrounding privacy than a continuous video recording.

### C. SMARTPHONE APPLICATION AND SENSORS

The phones were equipped with a custom data logging application[2] [27] as shown in Table 2. The screenshot shows 4 parts. The top part displays the status of the data collection. The second part shows the status of the Bluetooth connection with the other 3 phones. The application synchronizes the 4 phones using Bluetooth using a master-slave communication protocol. The participant uses only the master phone (i.e., the one in the hand) to interact with the application. The master phone will synchronize with the other 3 phones automatically. The third part shows the status of the most recent upload of the data to the server. The last part is the current annotation and label selection, where the user chooses the appropriate current activity (transportation mode), posture and location.

[2] Available at https://github.com/sussexwearlab/DataLogger

Table 2: Smartphone sensor modalities.

| | |
|---|---|
| 1. Accelerometer | 9. Ambient light |
| 2. Gyroscope | 10. Battery level and temperature |
| 3. Magnetometer | 11. Satellite reception |
| 4. Orientation in quaternions | 12. WiFi reception |
| 5. Gravity | 13. Mobile phone cell reception |
| 6. Linear acceleration | 14. Location obtained from satellites |
| 7. Ambient pressure | 15. Audio |
| 8. Google's activity recognition API | |

The Android application logs 15 sensor modalities that are available in the recording smartphone. For each sensor, we measured with the highest respective sampling rate as offered by the Android system.

### D. ACTIVITY SCENARIOS

An important task of the participants was to perform a balanced collection of the 8 transportation modes of interest, while interleaving them as much as possible with their daily professional or recreational routines. For instance, some participants used to do a regular evening jog; or cycled routinely to a sports ground; or travelled to London to visit a museum or meet friends. We encouraged participants to blend in the data collection with their normal routines for two reasons: first, it tended to produce a more realistic data collection; second, we believed it could increase the motivation of the participants, as the data collection procedure lasted a very long time (up to 7 months for one participant).

To further improve the quality of the data and ensure equal balance between the different activities, which is beneficial for machine learning approaches, we designed a protocol in which each participant met with the supervising researcher once a week in order to plan the activities of the following week. For this purpose, an activity scenario was prepared for each day. The activity scenario was shared online, so that both the participant and the supervising researcher had access to it at any time. At the end of each day, the participants were asked to use the same online spreadsheet to fill the amount of data collected for each activity for that particular day. This allowed the supervising researcher to check the status and control the data collection each day. Additionally, we have created a group chat between the research team and each of the participants. This allowed the participants to have real-time support in case of questions, doubts or issues.

### E. DATA COLLECTION PROCESS

The daily data collection procedure started with a check list that the participants had to follow to properly start the data collection. That included restarting all the phones and connecting them with Bluetooth. Next, the phones and the camera were synchronized by the first photo taken by the camera. That is, when the camera took the first photo, the participant had to provide a recognizable acceleration pattern - putting the phones on a table and hitting the table with the hand 5 times. Later, we used the photo and the 5 acceleration peaks (maximum values on the acceleration graph) to synchronize the smartphone sensors and the camera photos.

After the synchronization, the participants followed the outline of the daily activity scenario and performed and labeled the activities using the smartphone in the hand. In parallel they also kept a detailed diary (on paper or electronically), which at the end of the day was saved into the online spreadsheet. This diary later helped participants in the process of post-annotation using the annotation tool. At the end of the day, the participants again followed a check list to successfully end the data collection day. This included: the synchronization between the camera and the phones, filling the online spreadsheet with the amount of data collected for each activity, adding the detailed diary of the day to the spreadsheet, and putting the devices on chargers. Additionally, they were asked to upload the data to a remote server using their own WiFi.

After several days (typically 1 week) of data collection, the participants visited the laboratory to download the data, to check and correct the annotations with our annotation tool. First, the participant downloaded the data from the phones to a PC and removed private photos. Second, to further improve the quality of the labels, the participant performed additional data annotation. For this purpose, we have used an in-house annotation tool [28]. The tool loads the sensor data and the time-lapse video, aligns both, and displays them as a time series. An example illustration is given in Figure 3, in which at top is the time-lapse screenshot, and at the bottom is the accelerometer's signal. This allows the user to verify and correct the time stamps of the labels and to add additional annotations.

At the end of the measurement campaign, we performed a semi-structured interview to obtain information from the participants about the data collection process. For this purpose, we prepared a questionnaire, which included questions regarding the difficulty to use the equipment, the difficulty to perform different activities, and how to improve the data collection experience. The analysis of the questionnaires should help us to understand the perspective of the measurement subjects and to improve upcoming larger-scale measurement campaigns.

### F. REAL-TIME AND POST-HOC ANNOTATIONS

The smartphone application allowed the participants to perform real-time annotation of their activities and transportation options. Table 3 lists the main 8 activities together with the posture (sitting or standing), the location of the participant (inside or outside a building), driver or passenger when in a car, and lower and upper deck for the bus, which gives 18 labels in total.

Beside the main, on-device annotation, we asked the participants to post-annotate additional labels using their activity diaries and the time-lapse video. These additional labels allow precise description of the user's day and support a wider scope of research, such as recognition of eating, or

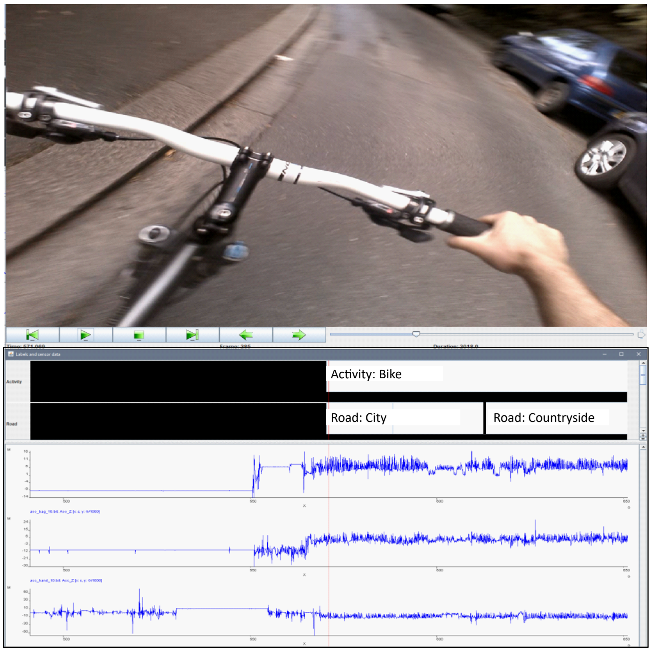


Figure 3: An illustration of the annotation tool with the time-lapse image (top) showing the participant cycling, the accelerometer 3-axial signal (bottom) and the annotations (middle). Here the annotation indicates the "bike" activity and road of type "city".

Table 3: The 8 main activities in the dataset.

| | |
|---|---|
| 1. Still: standing or sitting; inside or outside | 5. Bus: standing or sitting; lower deck or upper deck |
| 2. Walking: inside or outside | 6. Car: as driver or as passenger |
| 3. Run | 7. Train: standing or sitting |
| 4. Bike | 8. Subway: standing or sitting |

detection of social interactions, and others. These additional labels are:

- Road condition: city, motorway, countryside, dirt road
- Social interactions: yes if the participant was performing an activity together with a friend, no otherwise
- Tunnel: yes if the activity was performed in a tunnel or underground (subway), no otherwise
- Traffic: heavy traffic if the activity was performed during traffic peak hours with significant waiting in-line time, normal traffic otherwise
- Food: eating, drinking, or both

In total, there were 28 labels: 18 for the main activities and 10 for the additional annotations. Additionally, the null class marks activities that cannot be identified with sufficient confidence or are not in the annotated set. Some activities of interest may take place during these un-annotated periods but only for a very short period (e.g. a person may walk in-between two camera snapshots).

### G. DATA CURATION

The data which was downloaded from the phone was transformed into a format more manageable for future uses. We resampled all the motion sensor data (acceleration, gyroscope, etc.) of all 4 phones onto a common 100Hz sampling grid. This simplifies future applications of signal processing techniques on the data. We used the high accuracy timestamps, which the Android system assigns upon sensor data acquisition for this purpose. As these timestamps are reset to zero upon reboot, we exploit the network time to ensure time synchronization across the multiple phones. The resulting data is stored in plain text format, which allows easy import in various scientific tools. In addition, the released dataset contains the time-lapse video and a visualization of the user's traces and activities for each day.

### H. DATA QUALITY CONTROL

#### 1) Manual

We assessed data quality throughout the recordings as in Figure 4, which shows how much data is acquired from each sensor modality and allows visual identification of data loss. This allows to identify irregular data acquisition. This manual process has allowed us to identify initial issues with the "best effort" sampling strategy offered by Android phones to acquire WiFi and cellular reception during a first trial month of data collection. Quality control of the collected data is an essential step, which should be performed while collecting the data, so that if something is wrong one can correct it before the data is fully collected. Such a visualization is especially effective for sensors which have a regular sampling rate such as the motion sensors. Other sensors have a more irregular sampling rate defined by the low-level Android driver implementation. This includes battery (sampling rate about 1 per minute), light sensor (about 3 Hz), Google recognition API (sampling rate experimentally to be about once every 10 second, although the Google API reports that samples are provided whenever the activity changes) and location (sampling rate about 1Hz).

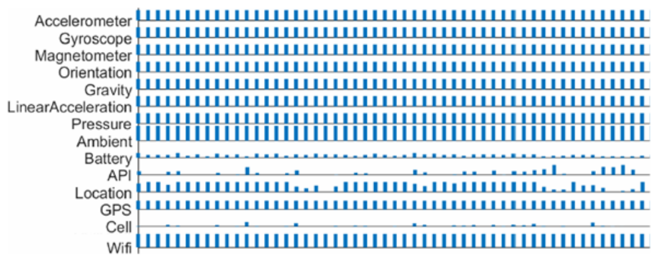


Figure 4: Amount of data collected for the 14 sensor modalities, plotted in time intervals of 10 minutes.

#### 2) Automatic

In addition to the visual inspection we employed quantitative automatic checks based on the assessment of a continuous "coverage metric". The coverage metric is the ratio between the received number of samples and expected number of samples. This value is 1 if the expected number of samples is obtained. It is higher or lower than 1 if respectively more or less samples than expected are received. This can be easily computed for sensors with a regular sampling rate (e.g. all the motion sensors and the pressure sensors at 100Hz). However, to make the system more adaptive to the different channels we automatically computed the expected sampling rate using the median of time intervals between samples. Therefore, the coverage metric is the total number of samples received divided by the expected number of samples, which is the duration of the recording divided by the median of the time intervals. We found this metric to be satisfactory for all sensors. Additionally, we automatically detect possible reboots of a phone. As the application restarts logging automatically if a reboot occurs this measure is used to identify if a user manipulation error occurred (e.g. long-pressing the power button leading to a reboot). Finally, we converted these metrics into a binary decision about the quality of each sensor channels for each phone. In the final dataset we release recordings for which we obtained a positive decision.

## IV. DATA ANALYSIS

### A. ANNOTATION ANALYSIS

Figure 5 shows the amount of the data collected for each of the 8 main activities and the contribution of each user to the total amount. Note that User 2 had difficulties with running and User 3 did not have access to a car, therefore they were not able to contribute to these activities.

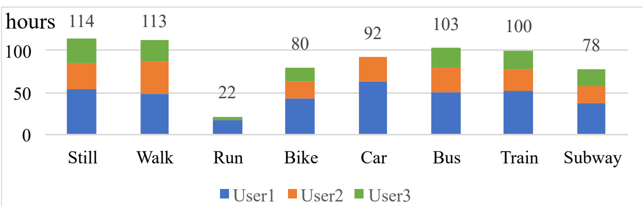


Figure 5: The amount of data collected for each of the 8 main activities in hours.

Figure 6 shows the breakdown for all the 28 labels and the contribution of each user to the total amount. Note that there is no data or very little data for the Bus-Up-Stand because it is not allowed to stand on the upper floor of busses in the country where the data was collected. Regarding the road conditions, 145 hours of data were collected while riding/driving in the city (labeled as "City road"), 37 hours on the motorway, 64 hours on country side roads and 19 hours on dirt road (this was mainly mountain biking performed by User 1). Also, there are 50 hours labeled as having a meal (eating and/or drinking), 84 hours of data labeled as social interaction, 49 hours of data being in a tunnel or in the underground subway (note that the subway in London has also parts in which it is over ground).

Figure 7 shows the difference between the amount of data annotated on a single phone in real-time (Raw: 752 h of annotations), after using the annotation tool to correct annotations (Annotated: 762 h of data) and the released data

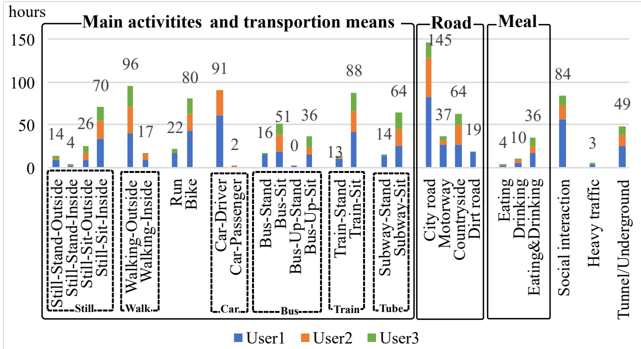


Figure 6: Breakdown for all the 28 labels and the contribution of each user to the total amount.

which is the data that passed the auto quality-checkup test, which means no reboot of the phones was detected (Release: 703 h of data). This figure shows that after annotation enhancement (Raw vs. Annotated) the amount of labeled data increased for some of the activities, e.g., Run increased by 2 h, Bike by 9 h, and Car by 11 h. This means the users corrected and extended the borders, i.e., the duration for these activities.

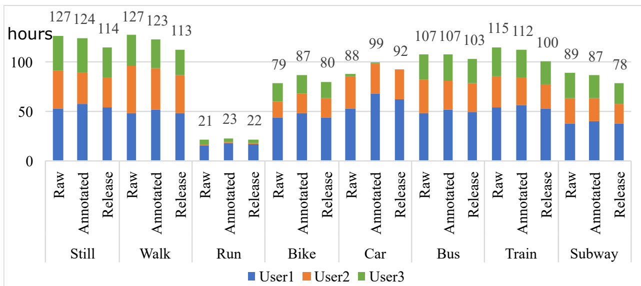


Figure 7: The amount of data before using the annotation tool (Raw), after using it (Annotated) and the released data (Release).

### B. SENSOR ANALYSIS

Figure 8 shows a heatmap of the GPS location data. On the left side are all the visited locations, and on the right side is the zoomed map on the Brighton area, where the University of Sussex leading this study is located. Note that most of the time the users were around Brighton, with regular visits to London. Also, User 1 had a 2-day visit in Liverpool. In the Brighton area, most of the time the users were around the city center, and the University of Sussex campus. In total, the participants travelled 17562 km.

Figure 9 shows the GPS coverage (i.e. the percentage of the dataset where one or more satellites are visible) according to each of the annotations for the main 8 activities. Because the GPS is logged every second, the coverage is calculated as a ratio between the total number of samples collected and the duration of the activities in seconds. The figure shows that the activities that are inside and the

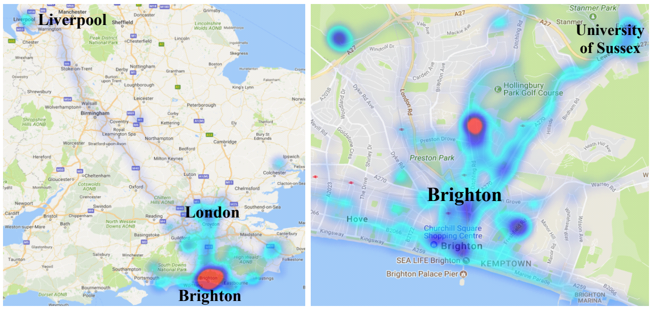


Figure 8: Heatmap of the location data. On the left are all the visited locations, on the right is the Brighton area.

subway have lower coverage. For the rest of the activities the coverage is above 95%, except for the train for which it is 87% and 78% for the sitting and the standing posture respectively.

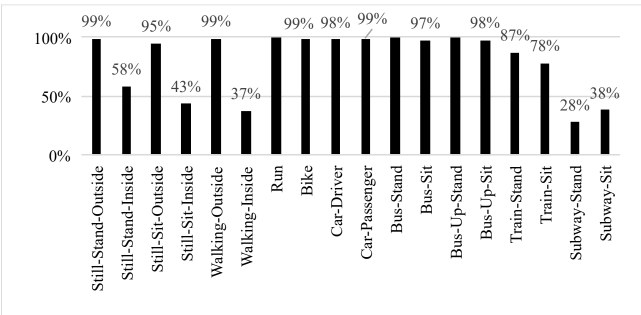


Figure 9: The GPS location coverage for each of the annotations. The activities which are inside, and the subway have lower coverage.

Figure 10 shows the percentage of time where N satellites are visible, with N ranging from no satellites received (10% of the time) to 23 satellites visible (never occurring). The percentage is calculated as the amount of GPS data collected for each number of visible satellites divided by the total amount of data. The analysis shows that 18% of the time there were 16 visible satellites, followed by 15% for 17, and 13% for the 15 satellites.

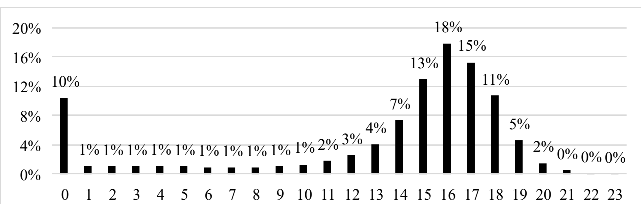


Figure 10: The number of visible satellites and the amount of GPS data collected in percentages.

Figure 11 shows the distance covered for each of the main activities. These results show that the distances for the walk, and run activities are significantly lower compared to the vehicle-based activities. The fact that the still activity has a non-zero distance covered is due to occasional moves which are short walks and GPS location jitter. The largest distance is covered by the train, which is closely followed by the car. Note that the subway in London has some sections that are above ground and only for these ones we calculated the distance which was 1416 km. During the underground sections there was no GPS data available.

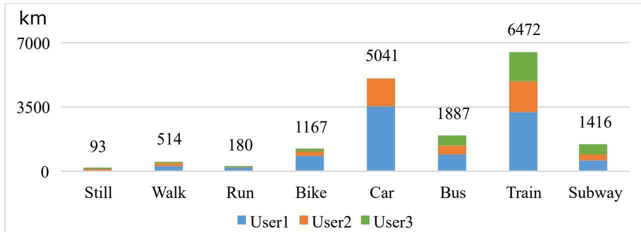


Figure 11: The number of visible satellites and the amount of GPS data collected in percentages.

Figure 12 shows the number of visible cellular base stations versus the amount of GSM data collected for each base station number. The percentage is calculated as the amount of GSM data collected for each base station number divided by the total amount of measurement that the smartphone retrieved from the cellular network. The analysis shows that 22% of the measurements performed saw 2 visible base stations, followed by 19% which saw only one base station and 18% of the measurement which saw 4 base stations. Note that we used only the recordings that have the cellular modem scanning set to 1Hz.

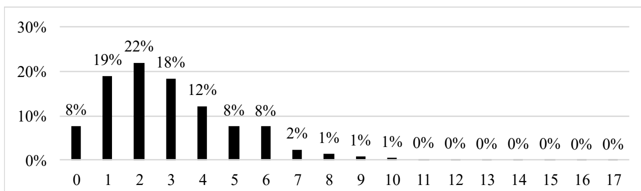


Figure 12: The number of visible GSM base stations and the amount of GSM data collected in percentages.

Figure 13 shows the number of visible WiFi access points (APs) and the amount of WiFi measurements collected from WiFi APs. The percentage is calculated as in cellular network where it refers to the amount of the WiFi measurements collected while scanning for visible APs. The analysis shows that 22% of the time there were 2 visible APs, followed by 19% for one AP, and 18% with 3 visible APs. Similar to the cells analysis, we used only the recordings for which we have set the WiFi scanning to 1Hz.

## V. EXEMPLARY MACHINE LEARNING APPLICATION: LOCOMOTION AND TRANSPORTATION RECOGNITION

One important motivation for collecting the SHL dataset is to create intelligent systems capable of recognizing the transportation mode of the user. In this section we show

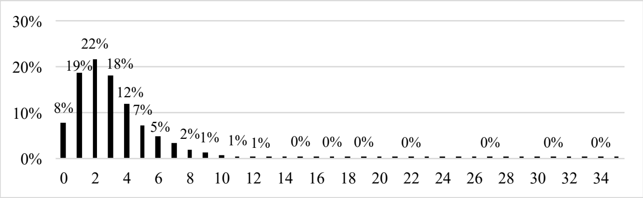


Figure 13: The number of visible WiFi access points and the amount of WiFi data collected in percentages.

an exemplary machine-learning pipeline performing transportation mode classification using the multimodal sensor data from this dataset. We use the data from User 1 with the four smartphone body positions (i.e. Hand, Torso, Hips, Bag), which amounts approximately to 360 hours per body position collected over 82 days (Fig. 5). For the analysis we considered only the 8 main activities: still, walk, run, bike, car, bus, train and subway.

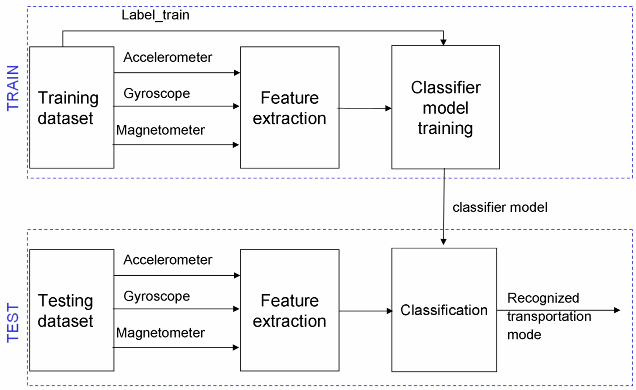


Figure 14: The processing pipeline applied to the SHL dataset. The data of User 1 is employed and divided into training and testing datasets using time-dependent 10-fold cross validation. The training dataset is used for classifier model training (top) and the testing dataset is used for performance evaluation (bottom).

Figure 14 illustrates the processing pipeline for transportation mode recognition. We split the data into 10 folds (approximately 8 days in each fold) and performed a time-dependent 10-fold cross validation (for each testing fold, we used the rest 9 to train the model). We used time-dependent cross validation and not the standard randomized cross validation because the sensors data are time-series, and we did not want to train and test on very similar and close in time data samples. The evaluation was done for each of the phones independently (train and test on the data originating from the same phone).

As suggested in [14], we divided the sensor data into frames with a sliding window of size 5.12 seconds with half overlap, and in each frame computed 7 features from the magnitude of the three motion sensors. For the accelerometer we computed mean, standard deviation, index of the highest FFT (fast Fourier transform value, and ratio between the first and second highest FFT values. For the gyroscope we computed mean and standard deviation, and for the magnetometer we computed standard deviation only. We employed a Decision Tree algorithm [29] to train a transportation mode classification model.

Figure 15 shows the pairwise comparison of the 7 basic features in the transportation mode classification task. In each panel, the x-axis and y-axis indicate the value of the feature while the class to which a sample belongs is indicated with different colors. This figure indicates how suitable are pairs of features to discriminate between the classes. For instance, the third feature is better at detecting the class car compared to the other features. The class run can be easily recognized with the 7 features.

Figure 16 shows the confusion matrix, the F1-score and the recognition accuracy obtained for each body position and also the overall performance, which is computed by merging the recognition results from all the four body positions. The four body positions achieve similar performance, with Hand showing slightly lower accuracy and F1-score than the other three. We speculate the reason for this is that the participants engaged with the phone in the hand more often during the travel, thus introducing more noise to the motion sensor data of the Hand phone.

The confusion matrices show that the first four activities (still, walk, run, and bike) are better recognized compared to the last four (car, bus, train, and subway). The motion of the smartphones during walk, run and bike is significantly higher than when the person is sitting or standing in the car, bus, train or subway, thus making the former four more distinctive than the latter four. There is mutual confusion between the motor vehicles (car vs. bus), and between the rail vehicles (train vs. subway). The reason for this is the similar motion patterns during these activities. Some confusion between still and the four vehicle activities (car, bus, train and subway) is also observed. Typically, some vehicle classes are recognized as still. This is possibly because the smartphones tend to be motionless when vehicle stops. For instance, bus is more frequently recognized as still than other vehicles which may be due to it stopping more frequently. In contrast, car is least recognized as still which may be due to it stopping less frequently.

In this example we mainly aim to demonstrate the usefulness of the SHL dataset to the research in locomotion and transportation recognition rather than maximizing the recognition performance. Even though, several interesting observations can still be made from experimental results, such as the limitation of using motion sensors alone (which are present in most of the related datasets) for distinguishing the basic 8 types of transportation modes and the influence of sensor placement on the recognition performance. To better distinguish the transportation modes, one should also include additional sensors such as GPS location data, pressure sensors, audio and similar. This would be one directions for future work.

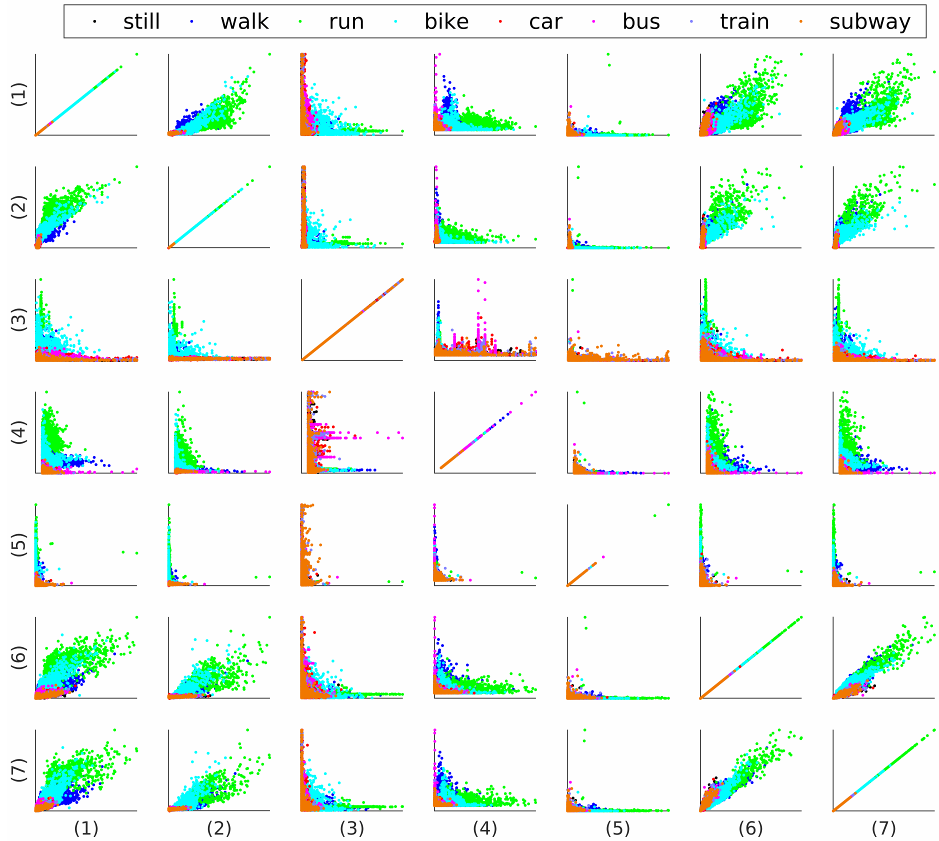


Figure 15: Pairwise comparison of the features for transportation mode classification. The seven features are (1)-(4): accelerometer (mean, standard deviation, index of the highest FFT value, ratio between the first and second highest FFT values); (5): magnetometer (standard deviation); (6)-(7): gyroscope (mean and standard deviation).

## VI. DISCUSSION

### A. CHALLENGES AND BEST PRACTICES

We gained a significant experience during the seven-month data collection campaign. In this section we report on the experience, the challenges and the issues that we encountered, and give ideas and suggestions on how to overcome them. We also report on the analysis of the answers of the participants to the questionnaire.

All the participants agreed that the smartphone application was intuitive and easy to use. However, we encountered few issues which were caused by the Android system itself. Sudden firmware update (from MHA-L29C432B156 to MHA-L29C432B182) for the 4 phones of User 1 caused some of the sensors to change their sampling rate. The accelerometer sample rate increased from a highly regular 100 Hz sampling rate to a variable sampling rate at about 200 Hz, and conversely the pressure sensor decreased from 100 Hz to 10 Hz. Also, the WiFi and Cell scanning were insufficient during some of the early recordings due to relying on a “best effort” scanning of Android. We modified the logging software to force reporting of WiFi and Cell at 1 second interval. While this forces the operating system to issue sensor events to the application at that rate, Android does not guarantee that this changes the underlying driver WiFi and cells scan rate. A possible solution would be to use a dedicated firmware only for data collection, without interruptions from the standard Android system.

All the participants agreed that carrying the equipment was comfortable enough in most cases, except for some situations such as during running. Additionally, participants agreed that the phones were too big (the Mate 9 has a 5.9" screen), especially the one in the hand that was used for annotation. A possible solution would be to use a smartwatch and voice commands for data annotation.

Regarding the camera, even though we initially thought that having a camera that would constantly take pictures would be felt to invade the privacy of the participants, the participants accepted it quickly. This may have been helped by using a "dumb" camera where the pictures stayed on the device under the control of the user, and the fact that users could remove all the unwanted pictures prior to annotation. Furthermore, the participants never encountered any unwanted situations during the 7-month period from people in their surroundings which could have been surprised to see their equipment.

The time-lapse video extracted from the camera, allowed

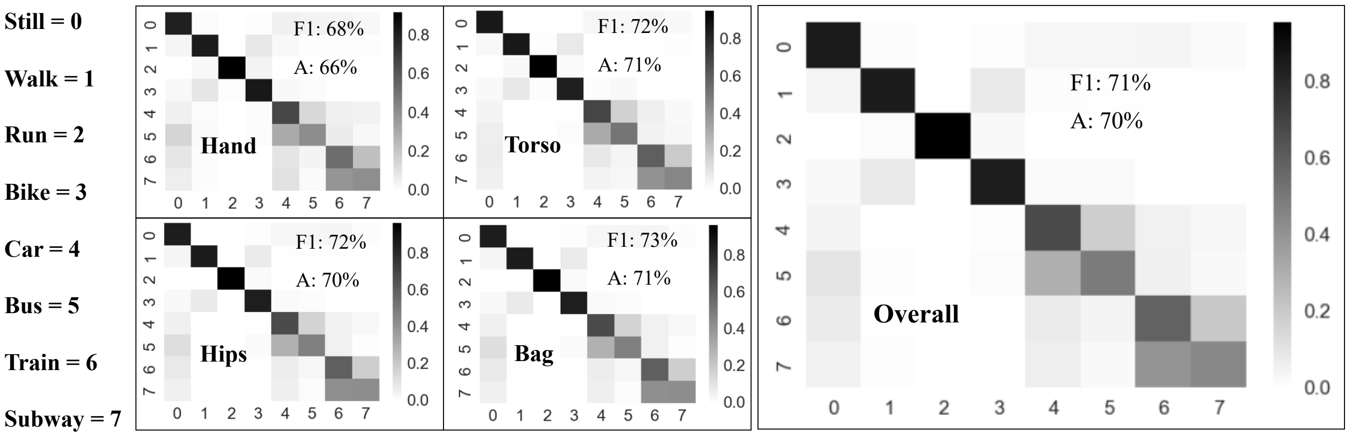


Figure 16: The confusion matrices for the 8 activities (still, walk, run, bike, car, bus, train, and subway), the F1-score (F1) and the accuracy (A) for each of the phone positions and the overall.

us to precisely and richly annotate the dataset with 28 labels in total. We tested 3 camera models and 7 cameras in total. Initially, we used the Snapcam ION lite camera [30], which takes 5 MP images (2592x1936). Then, we discovered that for the Users 2 and 3, the camera was not taking images at a constant interval, so we used another model: Drift Compass [31], which takes 8 MP images (3264x2448) every 32 seconds. Eventually, we realized that none of the above cameras were reliable enough (irregular time interval between images) and therefore we had to adapt the synchronization between time-lapse video and mobile phone sensor data in the annotation tool manually.

Regarding the main 8 activities, all participants agreed that the subway was the most boring activity and that they had to find something to do that does not require smart device and internet connection. Additionally, the running activity was the most physically demanding one, and it took some time for the participants to adapt to it.

Participants all agreed that the usage of the annotation tool was not easy nor intuitive and required extra time and effort to become proficient using it. One of the first participants in the data collection was tasked with shadowing new participants during annotation and helping them as needed. An update of the annotation tool is planned for future work.

The participants all agreed that planning the activity scenario in advance was very helpful, especially because it was online and shared between them and the experiment leader. Initially, we started with more detailed activity planning by providing start and end times for each activity, but after a few days we realized that providing a rough outline of the activity scenario was sufficient and gave space for improvisation and more realistic data collection.

If we were to extend the data collection with much more participants, some procedures could be improved to address the current issues and bottlenecks:

- Use smaller and more practical smartphones, especially for the one in the hand. An alternative would be to use a smartwatch.
- The usage of the annotation tool and the software should be improved so that the participants could do it with limited expert help. An alternative would be to have people trained only to annotate data collected by other participants. All the participants agreed that if the detailed activity diary was provided, they would be able to check and annotate other people's data.
- The planning of the activity scenario could be computer generated. Potentially, at the end of each day, a software could check what is the status of the dataset/activities collected and propose a few scenarios for the next day or week. The experiment leader would only intervene in cases where the participant cannot choose any of the suggested scenarios.
- A continuous data quality check-up could be devised to automatically raise warnings and notify the experiment leader if something is wrong. The scripts that we used for the offline automatic quality check-up and the automatic upload of data, should be modified and adapted to check the data continuously, every day.

### B. POTENTIAL APPLICATIONS

The dataset is highly versatile due to the multimodality and rich and high-quality annotations. In this paper, we showed how this dataset can be used for the automatic recognition of modes of transportation from the mobile phone sensors by using machine learning techniques. There are numerous enhancements possible to this work. For instance, it can be used for an in-depth analysis of user-independent or placement-independent recognition, therefore yielding a recognition system which is more robust to new users or to changes in on-body phone placement. The rich set of multimodal sensors also enables research in dynamic power-performance tradeoffs in activity recognition, where sensors may be duty cycled when power usage must be reduced, or multimodal sensors fused in larger numbers to increase recognition performance.

The dataset comprises the recording of the audio of the smartphone microphone. Computational audio scene analysis is another promising approach to recognize user transportation modes and the wider context of the user.

This dataset provides rich data for wireless sensor network and mobile communication research, in particular it allows to explore and predict wireless coverage (WiFi or cellular) according to transportation modes, displacement speed, or user location. This can enable useful applications in adaptive data streaming to minimize the impact when a connection quality degrades. Similar analysis can be made on Satellite reception in function of the user's transportation modes. There are numerous additional applications for this dataset. A few examples are:

- Road condition analysis and recognition. The dataset also contains labels about the road conditions, therefore it can allow research in this field, such as development of supervised machine learning model using the smartphone sensors to automatically detect he road conditions.
- Traffic conditions analysis and recognition. Similar to the previous example, the traffic conditions are also labeled, allowing researchers to use supervised machine learning techniques to train models to automatically recognize the traffic conditions using the smartphone data.
- Automatic detection of eating and drinking. This is also an interesting research topic, and can be potentially used in health applications such as calorie monitoring, diets, fitness applications, etc.
- Assessment of Google's activity and transportation recognition API in comparison to novel methods developed based on this dataset. Researchers can compare to a state of the art commercial model developed by Google, and can introduce improvements.
- Creating probabilistic mobility and locomotion models, which are commonly used in wireless sensor network research.
- Novel localization techniques using dynamic fusion of sensors. This is also a topic of interest to many researchers. Improving the localization of the user by using non-intrusive sensors can bring many applications to improve the quality of life of the users. For example, improving the indoor localization by using data fusion techniques for smarpthone sensors can be used for elderly monitoring applications.
- Image-based activity and transportation mode recognition, object recognition in everyday time-lapse video, context recognition from images (e.g. social interactions, having meal).

## VII. CONCLUSION

In this data collection campaign, we focused on obtaining a precisely annotated sensor-rich dataset, which is also representative of real-life. We encouraged participants to mesh their everyday routines with the data collection protocol as much as possible to ensure a dataset representative of everyday life. We used 4 high-end smartphones simultaneously placed on typical body locations to maximise the amount of data collected during recordings. We used a body-worn camera to help us further improve the accuracy of the annotations. To ensure the quality of the annotations, the participants used a dedicated tool to check the annotations and introduce additional ones after the data collection completed. In total 28 labels were annotated, including the mode of transportation, participant's posture, inside/outside location, road conditions, traffic conditions, presence in tunnels, social interaction, and having meals.

The dataset comprises 703 hours of recordings, which correspond to 2812 total hours of labeled data collected given the simultaneous recording from 4 locations. This took place over 7 months with three participants who engaged in 8 different modes of transportation in the south-east of the United Kingdom. Even though the number of participants is limited to three, our focus was on the quality of the collected and annotated data (28 labels in total), and on collecting real-life data over long period (2812 hours of labelled data and 17562 km of traveled distance collected over 7 months). This longitudinal data collection allows studies about changes in behavior and transportation usage over time. The full dataset will be made available to the community in batches over 2018 as privacy verification is completed. A preview of the dataset including 4x59=236 hours of data is already published at http://www.shl-dataset.org/. The full dataset will be released in the exact same file format. This allows studies done on the preview dataset to be seamlessly scaled up as the full data is released.

The large number of included sensors at different body locations, the diverse set of activities and their precise annotation make this dataset a valuable foundation for various research fields. Besides the automatic recognition of transportation modes which we exemplified here, it can be used for research in detection of social interaction, road conditions detection, traffic conditions detection, localization and sensor fusion. Further applications are expected based on the recorded sound and the camera data such as recognizing surrounding objects, or recognizing activities and the wider in which they occur. The GPS and WiFi and GSM data have valuable applications for indoor localization and they can serve as baseline for sensor-based localization.

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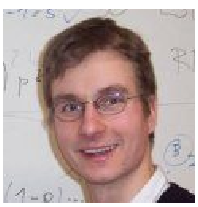

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